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ABSTRACT

A two-stage procedure for the analysis of pretest-posttest data was developed and illustrated. Data were reanalyzed from a quasi-experimental evaluation that assessed the effects of an intervention program to teach elementary school children aged 10 to 12 years to watch violence on television more carefully/critically. The treatment group consisted of 221 children, and the control group included 216 children. Use of a non-linear canonical correlation analysis and the CANALS computer program transformed the pretests and posttests so that they became linearly interrelated, and possible deviations from the linear model due to non-linearity were minimized. In a second step, the resulting optimally scaled set of pretest and posttest measures was analyzed by multiple analysis of covariance (MANCOVA) to measure program effects. The variance accounted for by the MANCOVA model appeared to be increased substantially by better prediction of posttest scores, by better estimation of the effect of the treatment, or by both. The advantages of the two-stage procedure are discussed. Five tables and 16 graphs illustrate the study. An appendix provides additional data in tables. (Author/SLD)

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LINEAR VERSUS NONLINEAR ANALYSIS IN THE MEASUREMENT OF EFFECTS IN A QUASI-EXPERIMENTAL DESIGN

Paper presented at the Annual Meeting of the American Educational Research Association (AERA), April 16-20, 1990, Boston.

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LINEAR VERSUS NONLINEAR ANALYSIS IN THE MEASUREMENT OF EFFECTS IN A QUASI-EXPERIMENTAL DESIGN

ABSTRACT

In this study a two-stage procedure for the analysis of pretest-posttest data is developed and illustrated. Data from a pretest-posttest control group design were firstly analyzed by nonlinear canonical correlation analysis. By this technique, the measure of the pretests and the posttests have been transformed in such a way, that they become interrelated linearly and possible deviations from the linear model due to nonlinearity have been minimized. In a second step the resulting optimally scaled set of pretest measures and of posttest measures were analyzed by (M)ANCOVA to measure program effects. The variance accounted for by the (M)ANCOVA model appeared to be increased substantially, either by a better prediction of posttest scores from pretest scores, either by a better estimation of the effect of the treatment or by both. It is concluded that the two-stage procedure indeed has important advantages.

INTRODUCTION

In quasi-experimental evaluation research the pretest-posttest control group design is a well-known and much used design. Many techniques of data analysis have been proposed for data obtained using such a design (see e.g. Cook & Campbell, 1979; Judd & Kenny, 1981). The most often used technique for the analysis of pretest-posttest data is the analysis of covariance (ANCOVA), with pretest measures as the covariate. This approach has the advantage that possible differences between experimental and control group will be accounted for statistically. In fact ANCOVA provides a statistical correction for possible pre-existing differences between the two groups. Because of the fact that using ANCOVA the within group variance will be reduced, the power of the statistical test will be increased. An alternative approach for the analysis of pretest-posttest data is a causal modelling approach, i.e. an approach based on structural equation modelling (Sörbom, 1975; Vooijs & Van der Kamp, 1989). An advantage of the latter approach is that it better meets the demands of the data and the design.

Both ANCOVA and the structural equation model are based on the general linear model. That is, it is assumed that the data are linearly related. For the analysis of pretest-posttest data by ANCOVA or by a structural equation model to be valid this implies a linear relation between pretest measures and posttest measures, and also within the set of pretest and of posttest measures. These linear relations are invariant under a linear transformation of the variables. Tests of significance are based on the assumption of linearity. And if this assumption is not met, the effects of a program can only be assessed less precise (Anderson, 1980). Moreover, the application of linear techniques only allows for the analysis of linear relationships. If nonlinear relations between variables exist, linear procedures cannot detect them, and consequently part of the variance will not be accounted for.

Linearity in the relationship between variables can be studied by studying the regression lines and by examining the residuals from linear regression. Departures from linearity may be due to outliers or to genuine nonlinearity. By removing outliers or by (monotonous) transformations the relations between variables can be linearized (see e.g. Chatterjee & Price, 1977; Draper & Smith, 1981; Mosteller & Tukey, 1977; Tukey, 1977; and Tabachnick & Fidell, 1989). It is not always clear, however, which of the possible transformations is optimal, and if so, in what sense.

Nonlinear multivariate analysis is the form of analysis to cope with the problem of nonlinear relations between variables (see e.g. Gifi, 1990). The central idea behind these techniques is the principle of optimal scaling, i.e. categorical data are transformed into

numerical data, such that the transform is optimal in some sense. Optimal scaling enables us to generalize many classical multivariate analysis techniques to their nonlinear, i.e. categorical, equivalents. In the present paper data from a pretest-posttest control group design are analyzed by nonlinear canonical correlation analysis (Van der Burg, 1988). The set of pretest measures and of posttest measures is optimally scaled by this technique, and the resulting optimally scaled variables will be used to produce new pretest and posttest measures that can be analyzed by ANCOVA to measure program effects. The statistical significance of these effects based on optimally scaled variables can than be compared with that of the effects of the non-scaled variables. Comparing both sets of results allows us to ascertain what can be gained by a nonlinear analysis of the data over a linear analysis.

NONLINEAR CANONICAL CORRELATION ANALYSIS (CCA)

Nonlinear CCA is a canonical correlation analysis with results invariant under certain nonlinear transformations of the data. More specifically, nonlinear CCA is defined as a method that looks for weight matrices A_1 (in our case for the pretest data) and A_2 (for the posttest data), exactly like classical CCA, but simultaneously looks for an optimal scaling of the data. In nonlinear CCA the data consist of variables that can take only a finite number of values, the category scores. These category scores of each variable are rescaled in such a way that the rescaled variables belong to a class of permitted transformations. The category quantifications, i.e. the rescaled values of the category scores, are optimal in the sense that they maximize the canonical correlations. The type of nonlinear transformations permitted is determined by the assumed measurement level of each variable. The measurement level can be discrete nominal, ordinal or numerical. A discrete measurement level implies that observations from one category remain in the same category under rescaling. The ordinal measurement level implies that the order of the original category scores should be maintained. And the numerical measurement level implies that only linear transformations of the data vectors are permitted.

The procedure used for the nonlinear analysis of pretest-posttest data is available in the computer program CANALS (Van der Burg & De Leeuw, 1983; Van der Burg, 1988). It belongs to the series of programs developped by the Department of Data Theory of the Leiden University, that used a so-called alternating least-squares (ALS) algorithm.

So the CANALS program performs a nonlinear canonical correlation analysis. It simultaneously scales the variables in the analysis optimally and minimizes a badness-of-fit function called 'stress':

$$\text{stress} = 1 - \frac{1}{p} \sum_{s=1}^{p} \lambda_s^2$$

with λ_s is the nonlinear canonical correlation coefficient for canonical variate s (s=1,...,p). The stress is equal to one minus the mean squared nonlinear canonical correlation coefficient. As with the classical canonical correlation analysis, a nonlinear canonical correlation analysis can also be performed in a univariate situation, i.e. where the first set contains one or several pretest measures and a measure for the treatment variable, and the second set only contains one variable, the posttest. Because the rank order of the measures on the pre- and posttests is usually meaningful, it can be assumed that these variables are measured on an ordinal level. The treatment variable (i.e. 'treatment' or 'no treatment') can be considered as a variable measured on a nominal level. If the treatment variable is indeed only dichotomous (i.e. 0 = membership treatment group ; 1 = control group), the level of measurement is not important. The reason is that the results of the analysis remain invariant under whatever nonlinear, monotonous or linear transformation, provided that the two treatment groups remain distinguished. CANALS scales the original measures on the variable in such a way that the posttest measures can be predicted optimally from the pretests and the treatment variable. With one posttest variable we deal with a nonlinear multiple regression analysis, i.e. a nonlinear canonical correlation analysis with only one variable in the second set. After the variables have been scaled optimally, an analysis of covariance can be performed with the measures on the pretests as the covariables or concomitant variables.

A multivariate application of CANALS proceeds in an analogous way. Now the second set consists of more than one measure on the posttests. The posttest measures are predicted from the corresponding measures on the pretests and on the treatment variable. Then the optimally scaled variables are submitted to a MANCOVA, with the pretests as the concomitant variables.

There are some important advantages in using optimally scaled variables for the pre- and posttests. The measures of the pretests and the posttests have been transformed in such a way (by CANALS), that they become interrelated linearly. These transformations minimize possible deviations from the linear model due to nonlinearity. This leads to a smaller error variance, and consequently the analysis of covariance leads to a more precise statistical testing. At the same time the measures on the transformed posttests are optimally correlated with the treatment variable. This means that differences in optimally scaled variables contributing to the treatment effect are maximized. This also increases the

sensitivity of the statistical test. One must keep in mind, however, that the optimally scaled variables are readily interpretable. If the size of the differences between original scores is meaningful, than the interpretation of the optimally scaled variables may turn out to be more problematic. But if the measurement scale is more or less arbitrary (and more often than not this will be the case), then interpreting the scaled variables should not become difficult (Tabachnick & Fidell, 1989).

DATA

As an illustration of the procedure proposed above, i.e. the use of CANALS in combination of (M)ANCOVA, data from a quasi-experimental evaluation study by Vooijs (1986) will be reanalyzed. The aim of this study was to assess the effects of an intervention programme to teach elementory school children aged 10 to 12 years to watch violence on TV more critically. The treatment group consisted of 221 children, the control group of 216 children. Before and after the intervention scores on three criterion variables were collected: (1) readiness to see violence; (2) approval of TV-violence, and (3) perceived TV-reality. Questionnaires have been used as an operationalization of the criterion variables. For the measurement of readiness and approval of TV-violence film fragments were used. All of the questionnaires used are highly reliable (Cronbach's alpha of 0.80 and higher). Also criterion-related validity of the instruments were satisfactory (Vooijs et al., 1984).

It was expected that children would become more critical towards violence in TV-serials due to the intervention program. That is, that they would judge violent actions on TV to be more serious than they would judge them prior to the program. And, furthermore, that they would less quickly approve of violent actions in TV-serials. In addition it was expected that the children would judge the violence in TV-serials less realistic. An ANCOVA and MANCOVA performed on the data of the whole sample of N=427, showed that each criterion variable showed a significant effect in the expected direction.

In the secondary analysis persented here, we confine our attention to the data of a subsample in which not all effects were significant. (This subsample consists of children aged 10 to 11 years of high socio-economic background; N=105.) The original variables have been coded in eight categories, and CANALS was used to analyze these categorical variables. The correlation between the original scores and the new scores is 0.95 or higher. Appendix 1 shows the data that have been analyzed. For each variable the frequencies for each category were recorded. Also for the treatment group (N=53) and

for the control group (N=52) the correlation coefficients are given between pretest and posttest scores, and the means and standard deviations.

CANALS AND ANCOVA

Firstly the results will be reported of CANALS in combination with ANCOVA. A CANALS analysis has been performed on each of the criterion variables, followed by an ANCOVA on the optimally scaled variables.

In each of the three CANALS-analyses the variables in the first set are the treatment variable and the pretest; the variable in the second set is the corresponding posttest. Pre- and posttest measures have been treated as if they were measured on an ordinal level. The results of each of the three CANALS-analyses are given in Table 1.

Table 1 about here

The canonical correlations for the criterion variables readiness and approval of TV-violence are 0.46 and 0.47, rather modest. The corresponding stress-values being 0.78 and 0.81, respectively. The canonical solution for the criterion variable perceived TV-reality turned out to be much better: canonical correlation coefficients equal to 0.79 and stress-value of 0.37. (If the pretest and posttest measure are treated numerically in CANALS, the respective stress-values are not much higher: 0.83, 0.85 and 0.43, respectively. This means that a linear and a nonlinear analysis of the data do not differ much.)

As a result of a canonical correlation analysis a so-called canonical variate for each of the three solutions mentioned is created, being a weighted sum of the pretest score and the score on the treatment variable. The canonical variate for the first set e.g. is equal to $0.39\ X_1 - 1.00\ X_2$; the canonical variate for the second set is, in this case, always equal to the posttest (with weight +1 or -1), the posttest being the only variable in the second set. The weights are both a function of the 'between-set' and the 'within-set' correlations. They maximize in fact the 'between-set' with respect to the 'within-set' correlations. If the 'within-set' correlations are high, then the weights are highly unstable.

The so-called structure coefficients in a canonical solution indicate the contribution of each variable to the corresponding canonical variate. It turns out that in the first two CANALS analyses the first canonical variate is mainly indicated by the pretest. In both canonical solutions the most important predictor of the posttest is the pretest. The

contribution of the treatment variable to the predictor is considerably less, taking into account the relatively low structure coefficients of -0.19 and -0.16. The third analysis shows a contrasting picture. Now the treatment variable is the most important predictor of the posttest. Clearly, there is a considerable treatment effect for this criterion variable.

Figure 1 shows the category quantifications for each of the three CANALS analyses. The initial category scores are plotted on the horizontal axis.

Figure 1 about here

The category quantifications are standardized for each variable. That is to say, they have been weighted in such a way that they add up to 0, and their sum of squares being 1.00. As already mentioned earlier, in the present case the scaling of the treatment variable does not matter, because this variable is dichotomous. For pretest and posttest variables things are different. If the measurements of these variables are on an interval level, than the transformation of the scores is linear. This means that in each plot a line can be drawn through the (X,Y)-values. For the pretest and posttest of readiness to see violence this does not hold completely, although the deviation from linearity is small. Instead of a linear transformation there rather is a nonlinear monotonous transformation. For the pretest the category scores 4 and 5 are combined, whereas the discrepancy between the scores 1, 2 and 3 are relatively small. The category scores 1 and 2 coincide for the posttest. The pretest and posttest for the variable approval of TV-violence also deviates to a certain extent from measurements on an interval level. High and low scores are less discriminated. This is also the case for the pretest and posttest measurements of perceived TV-reality.

To what extent the CANALS solution has been influenced by the presence of outliers in the data can easily be checked. The output of the computer program gives for each subject his or her score on the canonical variate. These scores are standardized. By plotting the canonical scores for the first set and for the second set, outliers can be traced. None of the three CANALS analyses showed outliers.

Pretest and posttest scores have been recoded on the basis of the CANALS solution for each criterion variable. That is, the initial category scores have been replaced by the category quantifications from the CANALS computations. After that an ANCOVA has been performed for each criterion variable, with pretest as the concomitant variable. Table

2 shows the results of each of these three ANCOVAs. Both ANCOVA results of unscaled as well as optimally scaled variables are displayed in Table 2. Both homogeneity of variance and parallelism of regression lines hold for both data sets.

Table 2 about here

Table 2 shows that comparing ANCOVA results for unscaled and scaled variables the predictive power of the criterion variable readiness to see violence has been improved in the latter case. The F-value of the concomitant variable increases from 19.72 to 26.98. Before optimal scaling (or transformation) the correlation coefficient between pretest and posttest is 0.40, after optimal scaling 0.46. The estimation of the treatment effect also has been improved. Initially no significant treatment effect has been found. After optimal scaling or transformation the effect is significant on a 5% level. The amount of variance accounted for by the treatment and covariate has increased from 16% (before) to 22% (after transformation).

For the other two criterion variables the ANCOVA results have only been improved in part after transformation. For the criterion variable approval of TV-violence the estimation of treatment effect has not been improved, the estimation of the effect of the concomitant variable has. The correlation coefficient between pretest and posttest turned out to increase from 0.38 to 0.43, while the variance accounted for by the ANCOVA model from 12% till 17%.

For the criterion variable perceived TV-reality there is no increase in the prediction of posttest scores from pretest scores (the correlation coefficient stays 0.50). The estimation of the effect of the treatment, however, has been improved. The amount of variance accounted for by the ANCOVA model increases from 57% to 62%.

In sum, ANCOVA results have been improved indeed after transformation (i.e. optimal scaling) of the pretest and posttest scores by CANALS. The variance accounted for by the ANCOVA model has been increased substantially, either by a better prediction of posttest scores from pretest scores, either by a better estimation of the effect of the treatment, or by both.

CANALS AND MANCOVA

After a univariate analysis of the evaluation data a multivariate analysis by CANALS in

combination with MANCOVA has been performed. First of all the second set consisting of the three posttests are predicted optimally from the first set of variables, viz. the three pretests and the treatment variable. Table 3 gives the results of this CANALS analysis.

Table 3 about here

The stress of the solution is 0.65. The 'numerical' CANALS analysis yields a stress-value of 0.71. It seems that not much is gained by a nonlinear multivariate analysis of the data. The canonical correlation coefficients corresponding to the three canonical variates are 0.79, 0.46 and 0.46, respectively. In this multivariate solution we have in fact taken the three previous CANALS analyses for each criterion variable separately together by taking account of their interrelationship. The first canonical correlation seems to be defined by the prediction of the posttest reality perception from the corresponding pretest and the treatment variable. The two other canonical variates are indicated by the prediction of the posttests from the pretests readiness and approval of TV-violence.

A multivariate CANALS analysis gives the category quantifications based on the so-called 'single approach' (Young et al., 1976). That is, the categories are quantified for all dimensions simultaneously. These category quantifications for the three dimensions (or canonical variates) are given in Figure 2.

Figure 2 about here

Comparing the category quantifications in Figure 2 with those of Figure 1 the differences appear to be rather small.

In a multidimensional CANALS analysis also outliers can easily be detected from the plot of the corresponding canonical scores of the first and second set. No outliers were found.

Next the original variables have been recoded on the basis of the three-dimensional CANALS solution. Then the optimally scaled variables have been analyzed by MANCOVA with the three pretests as the concomitant variables. Table 4 gives both the results of MANCOVA on the original variables and on the optimally scaled variables.

Table 4 about here

Clearly, the transformation of the variables based upon CANALS results in a better (multivariate) solution: F-values of both the simultaneous effect of the concomitant variable as well as of the treatment variable on the three dependent variables together have been increased. The variance accounted for by both MANCOVA solutions (i.e. 1-Λ, with Λ being Wilks's Lambda) increases from 44% to 52%. For the simultaneous effect of the treatment this increment is from 50% to 54%.

Univariate ANCOVA for each dependent variable separately shows what can be gained (see Table 5). After transformation the posttests readiness and approval of TV-violence can be predicted better from the three pretests. The F-values for the concomitant variable have been increased as compared with the F-values for the unscaled variables. The increment of the variance accounted for of the treatment effect is due to the improved estimation of the effect of the dependent variables readiness to see TV-violence and perceived TV-reality.

Table 5 about here

DISCUSSION

Performing CANALS in combination with (M)ANCOVA is in fact a two-stage procedure. First the original data have been screened and optimally scaled using CANALS, then (M)ANCOVA must detect the significance of effects. Similar procedures are proposed in recent developments in structural equation modelling (cf. Connell & Tanaka, 1987). Before the modelling the data are screened on linearity.

Our two-stage procedure is a two-step one, i.e. a combination of a nonlinear model (the first step) with a linear model (the second step). We hope to have shown important advantages of this procedure. In the first place it makes it possible to check the level of measurement of the pretest and posttest data, and to detect occurring outliers. An important advantage is that a optimization criterion is used, i.e. the posttest is predicted maximally from the pretests and the treatment variable. In addition possible deviations from linearity can be minimized by optimally scaling the original variables. In our

example the overall effect of optimal scaling is rather small. Nevertheless the improvement of the (M)ANCOVA results is appreciable.

Taking these advantages into account it is recommended to use our proposed two-stage procedure, i.e. nonlinear canonical correlation analysis followed by (M)ANCOVA, for the analysis of pretest-posttest data.

REFERENCES

Anderson, S., Auguier, A., Hauck, W.W., Oakes, D., Vandaele, W., & Weisberg, H.I. (1980). *Statistical methods for comparative studies. Techniques for bias reduction*. New York: John Wiley & Sons.

Burg, E. van der (1988). *Non-linear canonical correlation and some related techniques*. Leiden: DSWO Press.

Burg, E. van der, & Leeuw, J. de (1983). Non-linear canonical correlation. *British Journal of Mathematical and Statistical Psychology, 36*, 54-80.

Chatterjee, S., & Price, B. (1977). *Regression analysis by example*. New York: Wiley.

Connell, J.P., & Tanaka, J.S. (1987). Introduction to the special section on structural equation modeling. *Child Development, 58*, 2-3.

Cook, T.D., & Campbell, D.T. (1979). *Quasi-experimentation, design and analysis*. Chicago: Rand McNally.

Draper, N.R., & Smith, H. (1966). *Applied regression analysis*. New York: Wiley.

Gifi, A. (1990). *Non-linear multivariate analysis*. New York: Wiley.

Judd, Ch.M., & Kenny, D.A. (1981). *Estimating the effects of social interventions*. Cambridge: Cambridge University Press.

Mosteller, F.C., & Tukey, J.W. (1977). *Data analysis and regression*. Reading, MA: Addison-Wesley.

Sörbom, D. (1978). An alternative for the methodology for analysis of covariance. *Psychometrica, 43/3*.

Tabachnick, B.G., & Fidell, L.S. (1989). *Using multivariate statistics*. New York: Harper & Row publishers.

Tukey, J.W. (1977). *Exploratory data analysis*. Reading, MA: Addison-Wesley.

Vooijs, M.W. (1986). *Kritisch TV kijken: Een curriculumstudie* [Critical TV viewing: A curricular study]. Lisse, the Netherlands: Swets & Zeitlinger.

Vooijs, M.W., & Van der Kamp, L.J.Th. (1990). Het meten van programma-effecten: een vergelijking tussen covariantie-analyse en een multivariate analyse gebaseerd op het model van Sörbom [The assessment of program effects: A comparison between the analysis of covariance and a multivariate analysis based on Sörbom's model]. In: W.J. van der Linden & L.J.Th. van der Kamp, *Meetmethoden en data-analyse*. Amsterdam/Lisse, the Netherlands: Swets & Zeitlinger.

Vooijs, M.W., Van der Voort, T.H.A., Bakker, D., Gortzak, K.J.J.M., & Schoute, E.M. (1984). *Kritisch kastje kijken: een evaluatie-experiment. Deel II: Evaluatie-instrumenten* [Critical TV viewing: An evaluation study. Part II: Measuring instruments]. Leiden, the Netherlands: R.U. Leiden, LICOR/Vakgroep Wijsgerige en Empirische Pedagogiek.

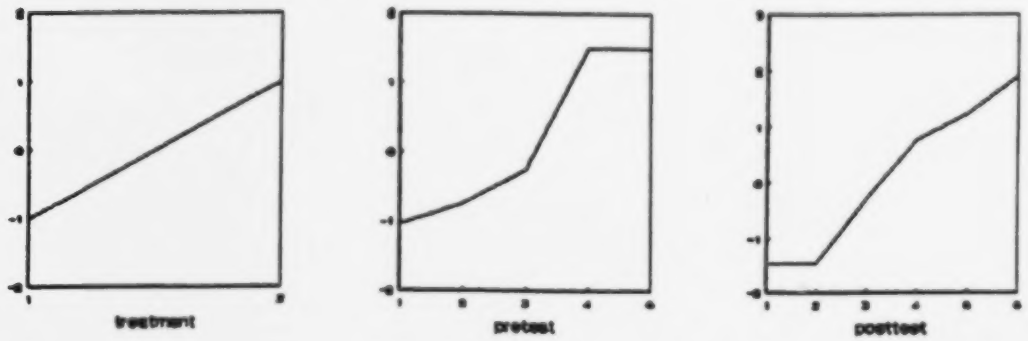
Young, F.W., Leeuw, J. de, & Takane, Y. (1976). Regression with qualitative and quantitative variables: An alternating least squares method with optimal scaling features. *Psychometrika, 41*, 505-529.

Table 1 CANALS solution for each variable* separately: canonical weights (cw), structure coefficients (sc), and canonical correlation coefficients (λ).

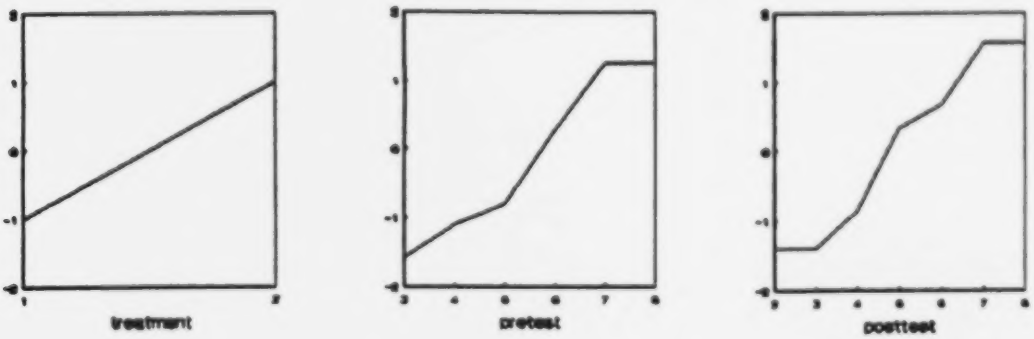
	CANALS 1 RV		CANALS 2 AV		CANALS 3 RP	
	cw	sc	cw	sc	cw	sc
treatment	-.39	-.19	.17	-.16	-.91	-.89
pretest	-1.00	-.93	-1.04	-.99	.46	.43
posttest	-1.00	-1.00	-1.00	-1.00	1.00	1.00
λ	.46		.44		.79	

* RV = readiness to see violence
AV = approval of violence
RP = reality perception TV-violence

CANALS 1: READINESS TO SEE VIOLENCE



CANALS 2: APPROVAL OF VIOLENCE



CANALS 3: REALITY PERCEPTION OF TV-VIOLENCE

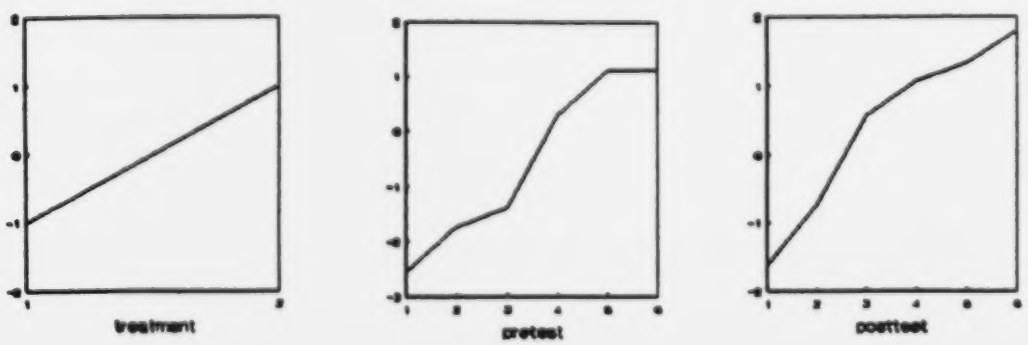


Figure 1: Category quantifications for each of the three CANALS analyses

Table 2 ANCOVA results for each variable separately: before and after transformation.

dependent variable	source of variance	df	before		after	
			MS	F	MS	F
RV	within cells	102	1.21	-	0.81	-
	covariate	1	23.93	19.72**	21.79	26.98**
	treatment	1	3.38	2.79	3.25	4.03*
AV	within cells	102	1.65	-	.83	-
	covariate	1	27.64	16.74**	19.51	23.41**
	treatment	1	.54	.33	.53	.64
RP	within cells	102	.60	-	.39	-
	covariate	1	19.96	33.39**	13.60	35.32**
	treatment	1	64.86	108.51**	53.92	139.98**

Table 3 CANALS solution multivariate for the three dependent variables: canonical weights (cw), structure coefficients (sc), and canonical correlation coefficients (λ).

	dimension					
	I		II		III	
	cw	sc	cw	sc	cw	sc
treatment	-.88	-.90	-.34	-.16	.10	-.17
pretest RV	.12	.30	-1.01	-.94	-.75	-.09
pretest AV	-.07	-.44	-.00	.56	-1.20	-.65
pretest RP	.42	.35	-.05	.03	-.62	-.50
posttest RV	.12	-.06	-1.21	-.97	-.72	.23
posttest AV	-.05	-.03	-.32	.51	-1.35	-.86
posttest RP	1.02	.99	-.08	.14	-.08	-.07
λ	.79		.46		.46	

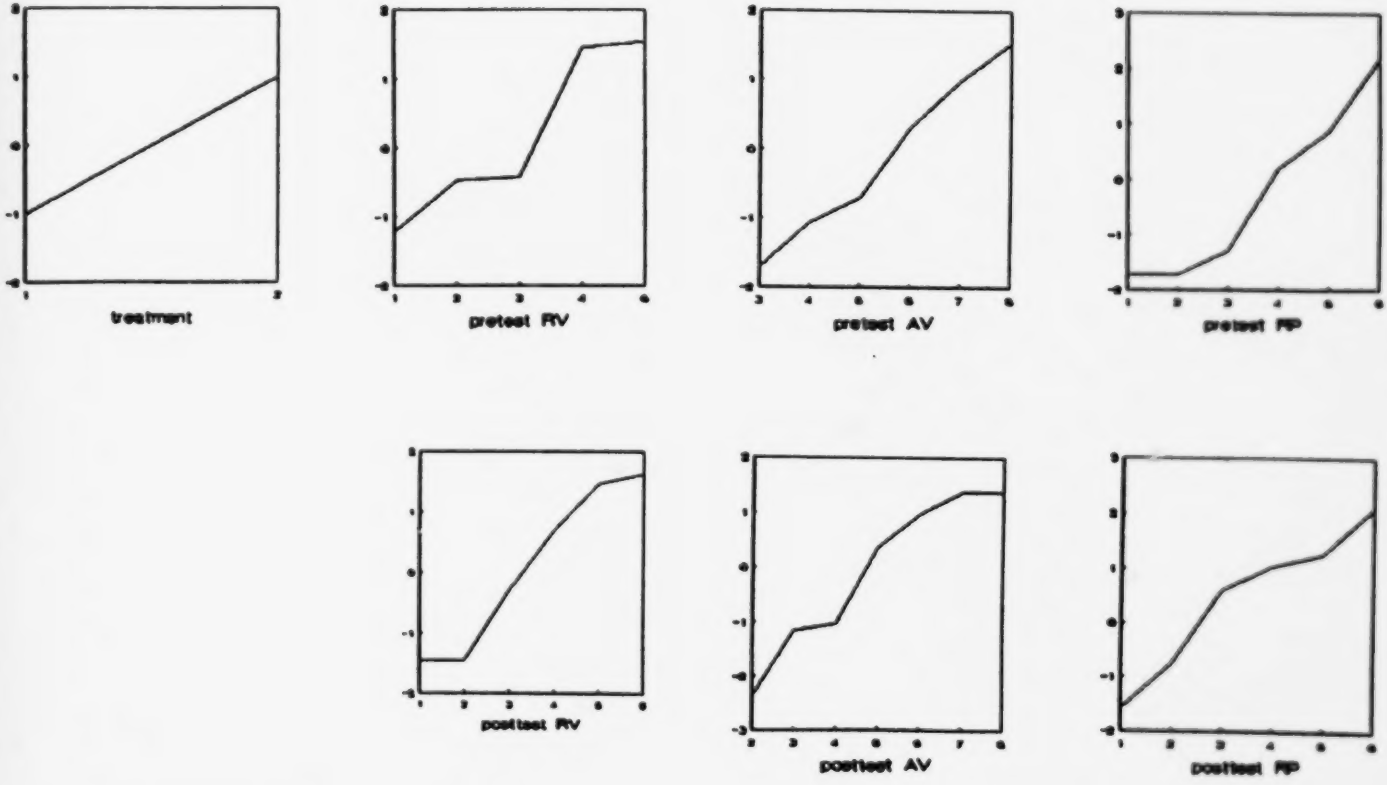


Figure 2: Category quantification for the three dimensional CANALS analyses

Table 4 MANCOVA results for three dependent variables simultaneously: before and after transformation, multivariate F and Wilks's Lambda

		before		after	
Simultaneous effect	df	F multiv.	Λ	F multiv.	Λ
Covariate	9;239	7.13**	.56	9.30**	.48
Treatment	3;98	32.60**	.50	39.01**	.46

Table 5 ANCOVA results for each dependent variable separately: before and after transformation.

		before				after			
Effect		df	MS_{error}	MS_{effect}	F	MS_{error}	MS_{effect}	F	
Covariate	RV	3;100	1.22	8.40	6.85**	.82	7.23	8.77**	
	AV	3;100	1.64	10.67	6.51**	.83	7.29	8.80**	
	RP	3;100	.61	6.68	10.97**	.40	9.07	10.09**	
Treatment	RV	1;100	1.22	4.13	3.37	.82	3.92	4.75*	
	AV	1;100	1.64	.73	.45	.83	.90	1.09	
	RP	1;100	.61	58.50	96.08**	.40	47.86	118.71**	

APPENDIX I

a. Frequencies for each category for the pre- and posttests (N = 105)

		category							
		1	2	3	4	5	6	7	8
pretest	RV	17	30	27	21	10	0	0	0
pretest	AV	0	0	9	15	21	29	18	13
pretest	RP	1	5	24	48	21	6	0	0
posttest	RV	9	16	31	35	11	3	0	0
posttest	AV	0	1	16	27	29	15	14	3
posttest	RP	14	35	27	21	7	1	0	0

b. Correlations between pretest and posttest scores and the means and standard deviations

Control group (N = 52)

			1	2	3	4	5	6
pretest	RV	(1)	1.00					
pretest	AV	(2)	-.79	1.00				
pretest	RP	(3)	.04	-.10	1.00			
posttest	RV	(4)	.53	-.49	.15	1.00		
posttest	AV	(5)	-.37	.41	-.13	-.77	1.00	
posttest	RP	(6)	-.10	.02	.60	.03	.10	1.00
		$\bar{X}$	3.06	5.21	3.92	3.23	4.81	3.54
		SD	1.16	1.36	.93	1.13	1.31	.92

Experimental group (N = 53)

			1	2	3	4	5	6
pretest	RV	(1)	1.00					
pretest	AV	(2)	-.69	1.00				
pretest	RP	(3)	-.09	-.04	1.00			
posttest	RV	(4)	.30	-.22	-.22	1.00		
posttest	AV	(5)	-.22	.35	.33	-.75	1.00	
posttest	RP	(6)	.02	-.06	.40	-.32	.28	1.00
		$\bar{X}$	2.51	6.13	4.00	3.38	5.00	2.00
		SD	1.22	1.41	1.02	1.26	1.44	.85

* RV = readiness to see violence
AV = approval of violence
RP = reality perception TV-violence